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What do energy modellers know? An ethnography of epistemic values and knowledge models

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ABSTRACT

This article considers academic energy modelling as a scientific practice. While models and modelling have been of considerable interest in energy social science research, few studies have brought together approaches from philosophy of science and anthropology to examine energy models both conceptually and in the applied sense. We develop a conceptual approach on epistemological ethics that distinguishes between epistemic values – such as accuracy, simplicity, and adequate representation – and non-epistemic values – such as policy relevance, methodological limitations, and learning – built into energy models. The research question is: how do modellers articulate and negotiate epistemic values and what does this imply for the status of models in scientific practice and policymaking? The empirical part of the article draws from ethnographic fieldwork and interviews amongst 40 energy modellers in university research groups in the UK from two complementary arenas: scholars preparing their PhD in modelling and scholars working in a large-scale energy modelling project. Our research uses ethnographic methods to complement themes recognised in earlier literatures on modelling, demonstrating what models and modellers know about the energy system and how they come to know it in particular ways.

1. Introduction

Energy social science and transitions research have shown considerable interest in models and modelling in recent years. Holtz and colleagues summarise a *model* as a representation of reality that formalises, simplifies, and stylises a part of that reality [1]. *Modelling* denotes practices where the boundaries of a modelled system – a target system – are designated and components of it are selected to the model based on research objectives. These generic descriptions open an important epistemological ethics issue on what modellers know about the energy system and how they come to know it.

Addressing this concern in appropriate depth requires a new approach, which we develop and advance in this article by building a framework to analyse ethical values in modelling. We focus on energy models in two ways: as methods that pursue new knowledge and as scientific practice in its own right. To study these objects, we combine tools from philosophy of science with anthropological and ethnographic studies of energy and infrastructures [2].

As philosophy of science has shown, the specifications and architectures of models have different kinds of qualities. Drawing from scholarly debate over recent decades, Diekmann and Peterson summarise certain kinds of qualities as *epistemic values*, including accuracy, simplicity, and adequate representation of the target system [3]. These values are called epistemic because following them is primarily done in the pursuit of new knowledge. Models can have several other built-in values depending on their specific purpose, such as learning about the target system's sustainability, reliability, or safety; or considerations on the limits of research methods. These can be described as *non-epistemic values* of models, because they are first and foremost aimed at objectives other than attaining new knowledge.

When used in practical problem-solving contexts, models integrate both epistemic and non-epistemic values, since applied models are shaped by specific problem framings. The overall quality of these models does not, therefore, rely only on epistemic criteria, but also on pragmatic solution-oriented considerations and on desired behaviours of the target system. This raises important and often overlooked questions on how epistemic values are embedded alongside non-epistemic values in the modelling process. Our article examines these issues by asking: *how do modellers articulate and negotiate epistemic values and what does that imply for the status of models in scientific practice and*

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policymaking? We address this question by focusing on the modelling of energy systems performance especially in the context of sustainable energy transitions and energy systems integration.

Numerous modelling techniques and approaches are used in energy modelling, drawing on different scientific disciplines such as engineering, statistics, economics, computer science, mathematics, psychology, and marketing. Efforts to address long-term energy goals often build on system models that simulate the performance of aspects of the energy system under specified possible conditions, policy interventions, or changing practices [4,5]. It is not straightforward to make such long-term evaluations (20 years or more) in an environment determined by complex interactions between technological, economic, social, cultural, and institutional spheres. In contrast with the more clear-cut possibilities for prediction in purely physical science domains such as classical mechanics, foresight in a complex domain such as whole energy systems is typically characterised by the interplay between different causal processes which may be too complex to be fully represented in any useful modelling process [6]. This problem is directly linked with epistemic and non-epistemic values: a major difference exists between modelling the energy system in the shorter, operational term, often grounded in empirical trends, compared with using longer-term planning and exploratory models to simulate envisioned (possible future) energy systems.

From an epistemic point of view, modelling and simulation as scientific practices raise challenging questions ranging from the representational value of models to the types of learning that models may enable [7]. In this paper, we take the main epistemological issues and points of view related to modelling and simulation as discussed in philosophy of science as a starting point for reflection. The empirical part of the paper (ethnographic fieldwork research by two researchers) examines modelling in practice in two arenas that complement each other. We studied the modelling practices by researchers from a large UK research consortium, the National Centre for Energy Systems Integration (CESI), alongside a wider group of academic energy modellers in the UK. The latter were mainly postgraduate students still developing their modelling skills and knowledge as part of their doctoral research. This strategy aimed to cover both skilled practitioners and those being brought into the modelling culture, to help us to uncover the relevant competences and skills needed to become a modeller [8]. Our general interest in modellers and modelling was inspired by recent anthropological scholarship that has examined the active use of models and how diverse kinds of model turn energy problems into objects of knowledge and action [9,10].

The rest of the article is structured as follows. Section 2 starts with a discussion of literature on epistemic values in modelling, while Section 3 sets out the materials and methods used. We use the philosophical questions and debates as a heuristic tool to explore the epistemic questions and concerns raised by energy modellers in their day-to-day practice (Sections 4–7). Section 8 summarises and discusses the consequence of our findings, highlighting the conclusions to be drawn from our ethnographic approach, complementing discussions on the prospects and limitations of modelling in the scholarly literature.

2. Literature review

Energy system models are formalised representations of a target energy system and can be described as vehicles for learning about the behaviour of these systems. But what kind of learning do they enable? To answer this question, scholars in the philosophy of science have elaborated general classifications of computer models as tools for knowledge development. Keller, for example, makes a distinction between three types of models [11]:

i) Models based on proven theories and mathematical abstractions of a real-world target system.
ii) Models whose calculations provide responses (data) in 'what-if' simulations, where the behaviour of a real-world target system is represented by a set of equations based on theoretical insights, but whose results cannot be verified empirically.
iii) Models that simulate the behaviour of entities, for example the simulation of artificial agents in agent-based modelling.

In a similar vein, the scholarly literature on energy social research and modelling has provided numerous classifications of energy models used by academics and policymakers. Scholars in Imperial College in the UK have recognised four different "modelling families": i) energy system optimisation models; ii) energy system simulation models; iii) power systems and electricity market models; and iv) qualitative and mixed-methods scenarios [12]. Another review by modelling scholars at University College London distinguishes between bottom-up models (which are best at addressing technological details of energy systems, such as MARKAL-TIMES); top-down models (which replace detail with understanding of large-scale energy-economy interactions, such as GEM-E3); and hybrid models that mix the two approaches [13]. These are by no means the only ways to classify energy models and these different classifications seem to work mainly for particular subgroups of modelling scholars. To pick just two more examples: Subramanian et al. divide energy models by their modelling approach (computational, mathematical vs. physical) and their field (process systems engineering vs. energy economics) [14]; while Lund et al. describe two archetypes of energy systems modelling, one being prescriptive investment optimisation or optimal solutions, the other an analytical simulation or alternatives assessment approach [15]. For our purposes, it is therefore firstly interesting to explore how energy modellers classify the models at their disposal, since this gives an indication about the goal-directedness of their modelling effort and how their approach to model typologies might inform their approach to making models (Section 4).

Secondly, it is well-known that many different models of the same target system can be constructed [16]. Parker points out that computer simulation studies perform model calculations based on numerical solving techniques, which can only approximate analytical model solutions [17]. Thus, while some energy models are used to solve physical equations, they may offer just approximations of physical laws. Furthermore, many energy systems models do not primarily aim to approximate physical laws but focus on systems dynamics such as representations of supply and demand. For these kinds of systems model, it is not the approximation that makes the models 'opaque' but the dependence of the model on large amounts of data and assumptions that may not be available to the modeller. In other words, these models have 'black box' characteristics [9]. The question in this context is, which approximations and kinds of epistemic 'opaqueness' are acceptable to energy modellers and why (see Section 5)?

Closely related to this is the representational value of models and simulations. Energy system models are constructed and used to learn something about the 'real-world' energy system. Yet the relation between simulations derived from running models and the target (the 'real energy system') is actively debated from an epistemological point of view. For a significant degree, this depends on how the 'target' is construed. Grüne-Yanoff and Weirich argue that,

> the target can be a prepared description of data, obtained by observation of real-world objects or events. These data are then 'prepared' by re-describing it in more abstract ways, for example, by curve fitting. The relation between simulation and world is then seen as a relation between the mathematical structure of the simulation (typically, a trajectory though state space) and the mathematical structure of the prepared data re-description. [18] (p. 24)

In other words, the typical target of a model or simulation is only a composite part of 'the real world'. In this view, the epistemic truth value of models and simulations is predicated on isolating the operation of certain causal factors from the complex interaction of factors in the real world.

The relationship between models and representation is also highlighted in energy social research literature. A frequently expressed view is summarised by Sovacool and colleagues when they state that "the reliability of energy models is often low because they are overly sensitive to cost assumptions and ignore other major drivers of energy policy and behaviour such as social equity, politics, and unforeseen technological advances" [19] (p. 95). In the energy models of buildings, this issue manifests in the "performance gap" critique, e.g., observing that realised energy savings from retrofits are often significantly lower than those "predicted by engineering models" [20] (p. 726). amongst the cited reasons for this kind of disparity between model and observation, well as factors such as improper installation and occupant behaviour, are "modelling inaccuracies". Such poor predictive capabilities lead some modellers and model users to advocate the use of modelling mainly as a tool to challenge existing assumptions or 'mental models' [21]. For our purposes, it is important to consider how the representativeness of energy models is understood and interpreted by energy modellers, and whether the way that epistemic values are articulated and related to non-epistemic values of models help to clarify this problem (Section 6).

Finally, Laes argues that it is useful to look at energy modelling and foresight from a constructivist perspective, which views foresight as a combined scientific-political practice [22]. In this reading, energy system models fulfil their role as 'boundary objects' [23], spanning the domains of science and decision making. Models such as these acquire different meanings in different social worlds, but their structure is still common enough to make them recognisable. The MARKAL energy model used in the UK, for example, gained influence by bringing together different professional communities with shared interests [24]. As science studies scholarship suggests, computer models are simultaneously scientific and political [25]: models have public and policy functions and are often explicitly made to be useful for the policy community [26,27].

One important function of scientific foresight exercises has been to protect scientists from accusation of bias or illegitimacy – because the exercises are situated clearly as 'official' or 'technical' objects of advisory science, and hence confusion with 'pure' research science is avoidable – while protecting policy makers from accusations of allowing technocratic intrusions into their domain of competency [28]. A known example that illustrates these two these principles is the UK Government's Aqua Book, which provides guidance on producing "quality analysis" for the government when using analytical models [29]. Indeed, an increasing amount of scholarship now exists on the policy implications and policy relevance of energy models [4,30-33]. Section 7 delves deeper into modellers' perspectives on the imagined profile of the policy users of their models.

3. Materials and methods

This article is based on empirical research carried out under the auspices of the National Centre for Energy Systems Integration (CESI), a 5-year research centre project funded by the Engineering and Physical Sciences Research Council (EPSRC) UK, and co-funded by industrial partners including Siemens, in partnership with distribution network operators and others.

CESI is a multidisciplinary consortium that includes social and economic sciences as well as engineering, mathematics, computer science, and other related disciplines. As stated in the project description: "The Centre …[aims] to understand how we can optimise the energy network, drive down customer bills and inform future government policy". [34]

The role of two authors of this paper was to conduct an analysis of the energy modelling process itself, and to bring social science knowledge to energy systems integration processes. In this paper, we draw on fieldwork that was conducted in two related modelling arenas. Firstly, the authors spent a term in university modelling groups, interviewing 28 engineering modellers conducting PhDs in engineering on energy-related modelling topics. We targeted 'novices' in our study as a way to make explicit the relevant "cognitive schemas, communicative competences, and social skills" [8] (p. 154) that modellers learn along with technical modelling techniques. Secondly, we interviewed 12 modellers who were directly involved in the CESI project, to learn about how modellers in a modelling institution – in this case, a large-scale UK research project – position themselves with regards to issues recognised in philosophy of science.

The interviewees were mainly based in engineering and physical sciences, though some had academic backgrounds that were not in energy systems. 13 of the subjects (one third) were women. Nearly all the subjects were project researchers, but a few of them were at lecturer level.[1] Our research design was inspired by the classic laboratory studies in Science and Technology Studies (STS) [35-37]. Like these studies, our enquiry aimed to establish a direct relation with expert actors, staying in their environment, observing and describing their practices, interacting with them, participating in their everyday routines, and striving to learn the meanings of their actions. Here this ethnographic approach involves going to where energy models are produced and the modelling tools configured as part of daily practice.[2]

4. A functional model typology

In this section, we will describe the different models deployed particularly in energy modelling and the types of epistemic questions that they raise. One foundational distinction within the CESI project that is found more generally in energy systems modelling, distinguished *operational models* and *planning models. Operational models* address the functioning of energy systems, such as transmission and distribution of electricity and gas under different infrastructural and resource conditions. Operational models draw on epistemic values of prediction and accuracy: terms such as particular, determination, and simulation are central for how the modellers understood these kinds of model. *Planning models* provide representations of future infrastructure and energy systems components. They were seen as more tentative than the operational models. Planning focuses on what future energy systems *could* possess and *might* operate. Planning models are aimed at exploration rather than determination of energy systems in models.

In considering the values incumbent in energy modelling, we noted another key distinction reported by energy modellers: between *physical models* and *statistical models*. In the case of energy demand models, *physical models* are based on physical theory: for example, how air moves in a building or how heat is transferred between materials.

[1] We stress an important point on the generalization of our findings from qualitative research. Most of the interviewees are from a small number of institutions and almost all of them had background in engineering and physics. If we were conducting a representative survey, this would be a caveat. However, our ethnography does not aim at *probabilistic* but at *theoretical sampling* [8] of the modelling process and its epistemic and non-epistemic values. This means that we chose the CESI project researchers and PhD students as our informants because they are relevant to address the research question. The article is not aimed at generalizing about what happens in all modelling research groups or the behaviour of all energy modellers everywhere. Rather, it aims providing new understanding on how modellers understand the ethical epistemic qualities of their models and relate those to non-epistemic values, drawing from and complementing existing literature on these topics.

[2] However, this research also differs from classic laboratory studies in one respect: our material spans more than one laboratory or other single sites of expert knowledge [38,39]. Several groups from various UK universities were included in the CESI consortium and in our study and most of the PhD students did not work for CESI but were based in a related engineering research group. In the field work, we were also interested in observing how situations in particular field sites interrelate to other sites that matter for models and their epistemic and non-epistemic values: such as the organization of research groups and relations to target 'end users' in industries and policy [36].

Statistical models are built from datasets often based on actual measurements of energy usage and the use of statistical techniques. They resemble an inductive approach to energy usage based on recorded patterns and practice and how these can be explained by statistical tools, such as models or combinations of them. A scholar in this area explained to us:

> Statistical modelling is basically where we try to understand some real-world problems first of all and then we try to collect the information or data. it could be qualitative or quantitative. We try to analyse those data, to understand what are the statistical characteristics of those data and then we try to develop the modelling framework.

This approach leads to an important methodological challenge: a model's 'quantitative' outputs (numbers) are often not the only scientifically significant outcome of that model. First, real-world problems determine what kinds of models are developed to begin with. Second, according to the modellers in the study, a number is often not a sufficient scientific result from a model. What is needed, rather, is a 'story' about what underlies these outputs and which inputs should have been modelled. This is particularly apparent in explanations of demand where the practices happening in a household in everyday life may go some way to explain why patterns of energy demand are shaped in a particular way [40]. Energy demands vary according to hour, day, month, and season. They are shaped both by what the demand modeller calls "deterministic physical processes" – such as lights turning on or off at a certain time during the day in a number of houses – and "stochastic processes" – such as visits from friends. A model output cannot reveal this composition of demand as such, but knowing the 'story' or a 'narrative' underpinning it can influence further model development.[3]

In sum, classifications of the models reveal a large roster of methodologies, forms of proof, knowledge bases, and research aims, such that the models have different epistemic qualities that need to be negotiated and articulated to the designers of other kinds of models. This adds to our overall interest in modelling as a scientific practice. Any modelling approach to complex problems will acknowledge that models cannot be treated as one entity but the modellers we studied developed typologies of models as part of their work. They also need to actively articulate and negotiate the limits of formal mathematical modelling and its interplay with sense-making activities (narratives, storylines). Design of models involved discrete decisions on the epistemic elements that a model would or would not address. Different models have related but potentially different relationships to representations of reality, different material impacts, and different potential target end users, themes which we discuss next.

5. Choice of models within the same functional category

In the context of energy systems integration, the limitations of current modelling practices have been clearly recognised. Their shortcomings include the inability of the most prevalent high-level static models to develop "integrated representations of the physics, engineering, social, spatial, temporal, or stochastic aspects of real energy systems" [50]. Various business and technological uncertainties, the effects of climate change, behavioural dynamics, and technological interdependencies posed further limitations to existing models, framed in epistemic terms: the models do not 'know' enough about these aspects of energy systems. Developing a model often starts from epistemic premises: what epistemic qualities will the model be able to address?

According to our interviews with the wider set of modellers, developing a model might mean first designing relevant relations between the knowledge known or data held, and the knowledge sought. This might be done in a hand-written sketch, for example, or on a spreadsheet, to help the modeller derive an equation for the function required. The choice of a tool – more accurately, a mathematical solver (i.e. software packages that solve equations or find the best statistical model to cover a dataset) has consequences for solving these equations. Modellers need to be aware of the approximations that the model makes and whether those are fit for the purpose of the research. The modelling tool has material implications for the processes that are being modelled and what can be known about them, such that an epistemic quality like 'accuracy' is adjusted in relation to the model's purpose – i.e. it is designed into the model. As a statistical modeller explained this, "when we do modelling, we start with some kinds of assumption about what kind of accuracy we are looking for".

For the PhD students embarking on modelling research, the modelling tool was sometimes passed on by PhD supervisors or immediate predecessors in the same research project, and sometimes they were guided by peers. One subject told us that modellers just have to select a modelling tool that others in the group know how to use so that help could be sought if the model did not work. That said, there were also occasions where the model was selected at will – such as the start of a PhD project, designing a new course, or sometimes replacing the model with another in the middle of an ongoing project. In these decision situations, a number of classifications were used though which modellers tried to resolve and understand this problem of what model to use.

One example of such distinctions appeared between open source models and proprietary models. The former was seen as more malleable for academic research; the latter made modelling easier, but were morally evaluated as "lazy". On the other hand, an open source model also introduced particular difficulties. They often had a smaller cohort of users and had gone through less product testing. As one senior modeller explained, "if you use an open-source model, the interface is probably more difficult to use, it's less efficient, it's more likely to crash." There is an indication of computational friction in running these models as this quote shows. Paul N. Edwards, studying climate modelling, refers to this friction as "the struggle involved in transforming data into information and knowledge" [51] (p. 84). In sum, the distinction between open source and proprietary models shows how choices are made by the modellers. These choices concern epistemic values: the convenience of proprietary models is contrasted with the epistemic quality of open-source models. But they also concern non-epistemic values: open-source models can contribute not only to pursuit of knowledge, but also to trust in how the models work [52] and a commitment to greater egalitarianism in science [53].

The choices that the modellers made were also decisions about epistemic qualities concerning the material effects of certain kinds of models. An existing model might be apt at representing certain qualities – such as high-level, static energy systems – but less capable of representing integrated, interactive, and complex energy systems. These epistemic values in modelling are reflectively clearly articulated by the modellers themselves.

6. Models and representation

In this section, we discuss further the notion of 'accuracy' amongst the expert modellers. Almost every modeller we spoke to explicitly acknowledged that the common critique of models as inaccurate predictive tools is not only a simplification, but also a misunderstanding [54]. We were told that planning models should not be used for predictive purposes, such as investment decisions, because they cannot

[3] Linking 'quantitative' and 'qualitative' knowledge is often addressed using the idea of a scenario, especially when future technological, economic, and social situations are concerned [10]. CESI participants have also been engaged in building their own scenarios, including so-called 'hybrid' scenarios that integrate narrative stories with modelled numbers. Scenario methodologies have been developed by several commercial actors such as Shell and are also widely used in energy research [41-49].

represent future uncertainty well enough. One of the developers of a planning model told that using these scenarios for predicting could even be worse than "no planning at all". This begs the question, if planning models are not be used for prediction and investment planning, then what are they for? Similarly, in the domain of energy demand, we were told that a building model cannot be used to predict how people's energy bills will evolve. This would constitute an 'improper' use of the model and give misleading results – the UK's Energy Performance Certificates (EPC) were cited as a notable example of inappropriate use. Instead of predicting bills, building models should be used to approximate the physics of a building and draw on that for understanding changes – such as changes in heating demand over time.

Models are representations of a more complex energy system. They can – sometimes but not always – be validated against empirical data to better resemble that system. For example, one of the work packages of CESI was explicitly called "validation and demonstration". This work package uses seven different demonstrator sites across the UK to "test specific energy system arrangements as a service" [55]. Our broader interviews with UK modellers uncovered several different ways to do model validation. These include laboratory experiments i.e. building what has been modelled (such as an engine) and measuring its behaviour in order to reconfigure the model. If that is not possible, as with future energy systems, one could also look at other modellers' results and validate the model against another model. If neither of the two are available, as in some life-cycle assessments of energy technologies, one could also validate the methodology: i.e. ask whether the model measures things in the way others do.

One of the modellers aligned with the CESI demand modelling distinguished between two kinds of approach to model validation. First,

> I'm developing the model for synthesizing the energy demand, so I do it at the individual profile level. So all the statistical property of empirical data should match with the synthetic data. And for that we checked, like, percentile distribution, probability density distribution, all the statistics such as mean standard deviation, all these things.

Second, "because these are the time series, you want to check some of the key properties of the time series: auto correlation function, partial auto correlation functions and those type of things, periodicity." These principles point to the importance of epistemic values: the knowledge of energy demand that the model synthesises should be in correspondence with empirical knowledge.

Yet, the relationship between models and representation was not only a problem solved by statistical methodologies. Models also must be updated to adapt to a changing reality in the present and changing expectations of the future. For example, current energy system models have to take account of new developments in energy storage, or radical changes in energy costs such as the recent dramatic decrease of UK wind energy spot prices. Current debates about the emergence of electric vehicles, and consequently the changing demand for EV charging capacity also loom very large for energy demand modellers, and they think a great deal about how this would affect the calculations in their models.

Models themselves therefore also have futures, and the future of a meticulously developed model may be deeply uncertain. To address this, research models are rarely 'finished', in that they are always in a state of development or revision. For the CESI operational models, for example, the components of energy systems were determined by the model structure, yet factors such as fuel prices, energy demands, and energy resources might still change in unexpected ways and subject the model to uncertainties. The planning models, running decades into the future, confronted uncertainties more widely. In these timeframes, energy technologies and associated social and economic issues could potentially change radically. This is another important expression of uncertainty. It demands the formal analysis of uncertainties, a topic of considerable recent interest amongst modellers and energy research [4,56-58]. For example, knowledge about the activities of institutional and political actors tends to be simplified by several current energy models, making their usage difficult and uncertain in the implementation of energy policies [5].

This section has shown that, from an epistemic point of view, models are not fatally compromised by being only partial representations of energy systems. That is to say, acknowledging the impossibility of fully accurate representation does not mean abandoning rigour as an epistemic quality. The wide acceptance of uncertainty analysis and scenario methods in the CESI consortium shows that the modellers, themselves, were reflective about the limits of the computer modelling. Yet what those limitations would mean for how their models can be legitimately used is a different question.

7. Policy and modelling

Rather than 'accuracy' or 'prediction', the modellers in CESI – and especially the demand modellers, whom we mostly refer to below – were considerably more interested in how their models get used and where. We heard modellers repeat George E.P. Box's quote, "All models are wrong, but some are useful." This 'usefulness' was measured often against hypothetical 'end-users', such as policy decision makers or industry companies. The bridge to these target end users of the models attracted systematic effort and discussion.

For instance, one informant had developed a similar model in two country contexts, in the UK and Bangladesh. The physics behind these two models was similar and the modelling tools resembled each other very closely. But the policy relevance had been markedly different in these two contexts. He expressed how satisfied he had been with the experience in the UK.

> Every day we will be, like, okay we did this. And they [the regional government] will be …working at different departments yet interacting with each other. … (They say) we want this, we don't want this, this is not right. What you have is an interaction. Then the model gets better.

The term, 'better model' here is revealing. With some exceptions, few modellers thought that their model is 'better' only if it becomes more accurate. Reality can be approached by validation (as noted above), but all models remain approximations. It would not be viable, or even productive, to try to develop a full, Borgesian 'correct' model of an energy system, a neighbourhood, or a building for example. On the contrary, a model could be physically 'inaccurate' or methodologically weak but still useful. A building modeller who had engaged in policy advisory panels expressed this:

> Weaknesses in methodology don't actually matter. That's what I get from those kinds of (policy-facing) discussions. And you start to think that actually, it doesn't matter if the answer is wrong because it makes something, provides somebody with the right direction when they are making a decision. It has failed as a physics tool but succeeded as a decision-making tool. That's actually fine. I have no problem with that at all. It is just that context, I mean because it is chasing rainbows to try to get a model to be accurate – a building model to be physically just literally accurate, empirically accurate – because that's not what it is for. It is for making better decisions around things.

This heavy stress on usefulness of models above truthfulness and the view that "weaknesses in methodology don't actually matter" also makes modellers shift political responsibility in their work. The more the modellers consider that modelling is about policy usefulness, the less they concern they seem to have around infringements of scientific accuracy in final decisions. The respondent's "that's actually fine" illustrates that for some modellers their goal may lie less in fighting for the strengths of their scientific methods than the importance of the issues raised by them being considered in eventual policy decisions. We could argue (provisionally) that by doing so some modellers consider themselves more as providers of policy-useful modelling input rather than adopting a political role in the debate to stress issues that may be in line with their personal values.

Nevertheless, the possible applications by different users, and representation of these end users and uses [59] were often raised in discussion as choices were made about next steps in the modelling process. At the same time, and more generally, the policy relevance of models seemed to be an inherent value of the models that many modellers regularly thought about. A workshop report by several CESI participants summarised this:

> Many of these research-needs under uncertainty analysis and elsewhere might be summarised as "analysis for decision making in the real world", and research and practice should be designed with this in mind. It is important to guard against matters such as collecting data for the sake of having a large dataset, or confusing optimality in the model world with a good decision in the real world – the real goal being to identify decisions which one has logical reason to believe are good ones in the real world. [60] (p. 9)

This interest in decision making, decision makers, and decision support, and the 'appropriate' use of models by putative decision makers, permeated the epistemic and non-epistemic values of many modellers that we interviewed and is of considerable interest in the modelling literature [4,30-33]. This has implications for understanding the epistemic values in these models – the models are 'valuable' when they are serviceable to the policy makers and can be used 'appropriately' in a policy context.

8. Discussion and conclusions

This article set out to consider how energy modellers articulate and negotiate epistemic values and examined what this implies for the status of models in scientific practice and their use in policymaking. We now discuss four main conclusions that highlight the significance of using epistemological analysis to think about models. While these findings confirm many common understandings of modelling literature, our aim here is to consider whether using an 'epistemic values' approach can shed new light on the ethical implications of modelling as scientific practice.

First, it is widely recognised that 'models' are diverse and fall into distinct traditions. The focus on epistemology casts light on what different kinds of models know, and in the case of energy modelling, that their knowledge may differ even within a single research project. An important frame for the CESI project that we examined was a typology of models, each with different epistemic qualities that need to be articulated to other kinds of models to couple the models together. Models used for infrastructure planning, for simulating an operational integrated energy network, or for measuring energy demands in buildings and dwellings have different methodologies, forms of proof, knowledge bases, research aims, and needs for data for their validation. They rely on related but distinct epistemic values. While the differences between their purposes, data-definitions, techniques, and outputs were recognised, the problem of divergent epistemic values was under-communicated. This leads to difficulties in reconciling what are, in fact, sometimes incompatible approaches, and explains why holistic energy system modelling remains elusive.

Second, the design of the models examined here involved discrete decisions on the epistemic qualities that models address. These epistemic qualities were reflectively articulated by the modellers, often starting with the initial designs of research projects. The choice of epistemic qualities of a model had material impacts on the modelling itself. For instance, some models are more apt for static high-level energy systems, some more suited for representing an integrated, dynamic, and highly interactive energy systems. Open-source computer models are more malleable and egalitarian for the scientific community, whereas proprietary computer models are less prone for computational frictions considering how they can be used. The ethnographic approach enabled us to dig more empirically into situations where these choices about epistemic qualities are actually made, complementing the existing literature where many model assumptions and data remain 'black boxed'.

Third, from an epistemic point of view, models can approach and approximate the energy systems, but are not meant to be accurate representations. The use of uncertainty analysis and scenario methods, coupled with aspirations to validate models with data, shows that modellers were critical of the limits of computer modelling. This observation is not new: there is a considerable amount of literature where modellers themselves critique computer modelling. Our contribution is in paying attention to the diversity of critiques of modelling. The limits of models operate potentially very differently when modelling, for example, a building, an energy network, or infrastructures of the future.

Fourth, we observed a widely shared interest in decision making, decision support, and the 'appropriate' use of models by these decision makers amongst the modellers we studied. This has implications for the epistemic values in these models: the models were seen as the best approximations of reality when they are serviceable to the policy makers and used in a policy context. The notion that energy models should be policy relevant is not novel, but we contribute to this issue by showing how modellers themselves articulated this value. We have demonstrated how modellers saw policy relevance as a key form of legitimacy for their models and how concerned they were when they could not engage policy makers to put their models into legitimate use. The needs of these 'end users' often built on the common sense of the model designers – using general assumptions about how 'policy decisions' are made, rather than in-depth knowledge of governance practices.

Our observations open areas for future research. This article was based on ethnographic interviews and observations on important sites, namely research groups whose task it is to develop energy computer models. This methodology provides an often-overlooked view into the construction of modelled knowledge in scientific practice. It remains an empirical question which values – epistemic or non-epistemic – were embedded in other contexts, such as industrial advisory board discussions, the drafting of research grants, applications submitted to ethics boards, or policy-level meetings between academic and business leaders. Thus, our research provides a starting point for wider-ranging multi-sited ethnographic analysis where fieldwork could be used to chart the translation of values of modelling across different sites.

Further empirical research is needed, in particular, on the actual use of energy-system models in governance contexts. Our findings suggest that training in governance would also be appropriate for engineers working in energy-policy related modelling. Modellers could bring policy and modelling closer together via methods developed in technology and innovation studies. Co-creation approaches to modelling might allow diverse end users to contribute to model design from the start, defining key terms or uses. This would mean not only making assumptions about which policy decisions relate to modelling but opening that question for empirical inquiry and engagement from policy makers, thus thinking anew the epistemic qualities in energy models.

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